

DEVELOPMENT OF MALAYSIAN ENGLISH LARGE VOCABULARY CONTINUOUS SPEECH RECOGNIZER USING ACOUSTIC MODEL ADAPTATION

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ABSTRACT

This research project aims to develop Malaysian English Continuous Speech Recognition system by adapting US English acoustic model with Malaysian English speech corpus using Maximum a posteriori reasoning (MAP) and Maximum Likelihood Linear Regression (MLLR). During feature extraction stage, the Mel-Frequency Cepstral Coefficients (MFCC) technique was used. The Hidden Markov Model was used as the back end pattern comparison technique. For the purpose of implementation, the CMU Sphinx toolkit, which includes Pocketsphinx and Sphinxtrain as well as an acoustic model, was used to develop a speech recognition system for Malaysian English. Malaysian English speech sample will be recorded and transcribed to produce the training database required for acoustic model adaptation. The adaptation speech corpus were collected from a number of speakers. The outcome of this research could increase the application of Malaysian English speech recognition in Malaysia due to accent problem. The graphical user interface for Malaysian English Speech Recognition system was created with PyCharm Community Edition and Python 3.9 to make it easier for the individual consumer usage. As a result, speech recognition systems that have gone through the MAP adaptation had the best performance. Its average word error rate achieved was 32.84%. average word recognition rate was 72.52% and average sentence error rate was 78.89%.

Keywords: *Speech Recognition, Acoustic Model, MAP, MLLR, Pocketsphinx*

1.0 INTRODUCTION

Speech is a form of language-based individual vocalization. The audio within each linguistic vocabulary is formed by pronunciation arrangements of vowel and consonant tones. While using several terms in their linguistic context as vocabulary in a linguistic dictionary in accordance with the grammatical restrictions that regulate the role of lexical parts of speech (Houghton Mifflin, 2015). Speakers may use pronunciation, inflection, volume of voice, rhythm, and several other non-representational or vocabulary elements of vocalization to express meaning in several specific deliberate speech acts, such as telling, announcing, questioning, convincing, and guiding. Speakers unwittingly express many facets of their social status in their speeches, including gender, aged, point of birth, cognitive abilities, psychological condition, physio-psyche condition, background, or knowledge, etc. Several components of speech are investigated by researchers, including speech processing and voice detection (Houghton Mifflin, 2015). Voice duplication, voice defects, and the failure to translate hearing speaking terms into the vocalizations required to reproduce them are all examples of these. This is important for kid's vocabulary development and mind development in various fields. Sociology, theoretical physics, information science, sociology, software engineering, forensic linguistics, ophthalmology, and sound systems are all fields that research speech. Speech is related to linguistic knowledge, which can distinguish from

spoken language in terms of pronunciation, grammar, and phonology, a disorder known as diglossia (Houghton Mifflin, 2015; NIDCD, 2021).

The conversion of individual voice signals into vocabulary or commands is known as speech recognition. Speech recognition is dependent on the sound of a person's voice. That is a subdivision of information processing and a significant research path in speech signal processing. Software engineering, machine learning, digital signal processing, information processing, sound systems, linguistics, and cognitive science all play a role in speech recognition study. It's an interdisciplinary, all-encompassing field of study. Based on research objectives and restrictions, numerous research areas have arisen. These fields could be separated into isolated words, connected words, and continuous speech recognition systems, depending upon the needs of the presenter's style of communicating. The above fields could be classified into speech recognition systems for individuals and non-specific persons depending on the level of reliance on the person speaking (Science Direct, 2021). These could be categorized into small vocabulary, medium vocabulary, big vocabulary, and infinite vocabulary speech recognition systems based also on scale of their pronunciation. The concept of the voice recognition model is predicated on information processing, according to the speech recognition model. That aim of speech recognition is to use phonology and textual data to convert a received signal feature vector pattern into a series of text. A full speech recognition system involves information extraction technique, the acoustic template, a language model, and a search method, as according to configuration of a speech recognition system. A multifaceted information processing system is exactly what a speech recognition system is. Researchers use different recognition methodologies for specific speech recognition systems. However, the simple concepts are the same. Function abstraction is applied to the obtained speech recognition. The template database system collects and processes the speech information received by the system. The voice information retrieval module recognizes speech samples based on the template database, and then calculates the segmentation results (Science Direct, 2021).

2.0 LITERATURE REVIEW

Speech recognition is the process of converting spoken words into text. Any computer or software programme with the ability to accurately recognise and capture terms and phrases has this ability built in. These spoken language words and phrases are transformed and converted into different digital formats using a range of external hardware equipment such as microphones and voice recorders.

Speech recognition systems allow a computer to carry out human-spoken commands, perform automatic translation, and generate print-ready dictation. The microphone receives the sound signal, which is then transformed into a digital signal by the system hardware. The analysis tool of a speech recognition device uses the produced digital signal as input to extract and recognise the differentiated phoneme. Several of the lowest units of sound is the phoneme, which distinguishes the sound of one word from that of another. Nevertheless, most of the voice of the phrases are similar. As a result, the software must depend on context to distinguish the right punctuation among all these similar sounding words (Abhang, Gawali and Mehrotra, 2016).

2.1 Process of Speech Recognition

Those two most popular strategies to speech recognition could be classified as "template matching" and "feature analysis." If used correctly, template matching is really the quickest method with the highest precision, but it often would have the most drawbacks. That individual should first say a word or statement into a mic, just like in any technique to speech recognition. An "analogue-to-digital (A/D) converter" transforms the electric signals from the

receiver into digital form, which is then loaded into memory. The machine aims at comparing the input with even a digitalised audio model or prototype, which has an established definition to evaluate the "meaning" of the sound input. This approach is somewhat similar to using a button to enter commands. That software includes an input framework and provides a simple constraint declaration to try and adapt the model to the real input (HITL, 2021).

2.2 Feature Extraction

The key component of a speech recognition program is feature extraction. These are regarded as the program's beating heart. The aim would be to extract features through the source voice signal which will aid the device in recognising the user. That intensity of the source signals is compressed by feature extraction without affecting the voice signal's strength. Furthermore, it attempts to minimise the loss of data kept among the terms during this point. That aids throughout the consistency comparison of its acoustic model's distributional assumption.

Mel frequency cepstral coefficients (MFCC) (Alim, 2018; Vergin, R., O'Shaughnessy, D. and Farhat, A., 1999; X. Zhou, D. Garcia-Romero, R. Duraiswami, C. Espy-Wilson and S. Shamma 2011; Muda, L., Begam, M. and Elamvazuthi, I. 2021) were first proposed for recognizing idiomatic phrases in consistently voiced statements, but not for determining the user. The MFCC algorithm is really a simulation of the living thing listening process that serves to theoretically enforce the ear's working theory, assuming also that living person ear is really an effective voice recognition system. That MFCC models are based on a known difference between the essential bandwidths of the living person ear and frequency filtering distributed sequentially at lower frequency. That pronunciation critical characteristics of the voice signal were preserved by doing this logarithmically at higher frequency. Sounds of various frequencies are generally used in voice signal, with every voice having its own frequency. The Mel measurement is used to calculate arbitrary pitch. Approximately 1000 Hz, that mel-frequency level contains linear frequency spaced, and over 1000 Hz, these have linear interpolation frequency width. The 1000 mels was its pitch of even a 1 kHz voice at 40 dB over the perceived detectable level, which is applied as a level of comparison.

That MFCC algorithm depends upon signal dissolution using a wiener filter. That MFCC generates a discrete cosine transform (DCT) of even a particular logarithm of its simple terms power also on Mel frequency range. Under safety purposes, the MFCC is being used to classify travel arrangements, contact information, and speech recognition. With improved robustness, several improvements to the simple MFCC methodology are being suggested. Besides instance, while implementing the DCT, raise the log-mel-amplitudes to a suitable capacity. That alone lessens the detrimental effects of low-energy materials (Alim, 2018; Vergin, O'Shaughnessy and Farhat, 1999; Zhou, Garcia-Romero, Duraiswami, Espy-Wilson and Shamma 2011; Muda, Begam and Elamvazuthi, 2021).

The Mel Frequency Cepstrum parameters of MFCC are constructed from a distorted frequency range focusing on individual perceptual experience. Its first stage in MFCC processing is windowing the voice signal which divides these into layers. Although the high frequency formants method would have a lower amplitude than the low frequency formants, the high frequencies are stressed in order to achieve a comparable amplification for both formants. The energy spectrum within each frame is determined using the Fast Fourier Transform (FFT) upon windowing. Following that, Mel-scale filter system work is performed on the energy spectrum. In order to determine MFCC parameters, the DCT is added to the voice signal once the energy spectrum being converted to log field. Is indeed the equation for determining Mels for every frequency (Alim, 2018; Vergin, O'Shaughnessy and Farhat, 1999;

Zhou, Garcia-Romero, Duraiswami, Espy-Wilson and Shamma 2011; Muda, Begam and Elamvazuthi, 2021).

$$mel(f) = 2595 \times \log_{10} \left(1 + \frac{f}{700} \right)$$

Where Mel (f) represents the frequency (Mels) and f represents the frequency (Hz). The below formula is used to measure the MFCCs.

$$C_n = \sum_{k=1}^k (\log S_k) \cos \left[n \left(k - \frac{1}{2} \right) \frac{\pi}{k} \right]$$

there k defines the number of Mel Cepstrum parameters S the filter bank production, and C the last MFCC approximation.

Figure 1 shows the block diagram including its MFCC module. That encapsulates all of the procedures and procedures required in obtaining the necessary correlations. That low frequency area could be essentially denoted by MFCC, while the high frequency field can indeed be efficiently denoted by MFCC. This one can approximate and define vocal folds resonances using formants throughout the low frequency region. That is widely acknowledged as a front-end technique for popular Speech Recognition implementations. These have minimised noise disruption uncertainty, provides minutes process instability, and is simple to develop. Often, whenever the useful in the evaluation are balanced and coherent expression, it is a good demonstration for voices. It could also derive data through processed signals with a peak frequency of 5 kHz. This covers the bulk of the power found in human-made voices (Alim, 2018; Vergin, O'Shaughnessy and Farhat, 1999; Zhou, Garcia-Romero, Duraiswami, Espy-Wilson and Shamma, 2011; Muda, Begam and Elamvazuthi, 2021).

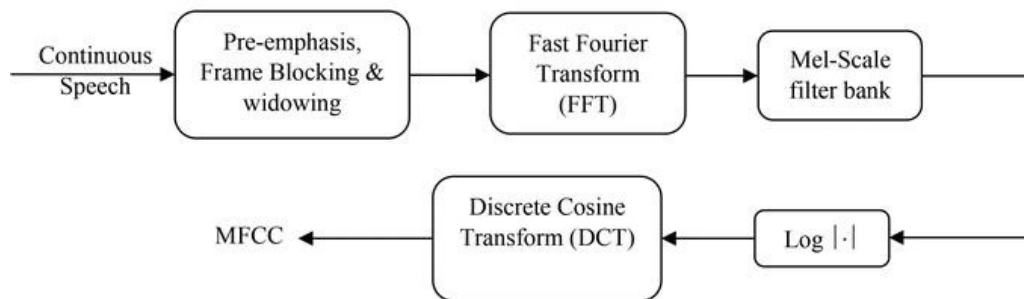


Figure 1. Block Diagram of MFCC

In several pattern recognition difficulties concerning living person speech, cepstral coefficients are shown to be correct. They are commonly utilized in numerous speech recognition and presenter detection. Those certain formants should be over 1 kHz, and indeed the wide filter width throughout the high frequency region does not effectively account for them. Throughout the presence of ambient noise, MFCC functions may not always be reliable, and they are not very well equipped for generalisation (Alim, 2018; Vergin, O'Shaughnessy and Farhat, 1999; Zhou, Garcia-Romero, Duraiswami, Espy-Wilson and Shamma 2011; Muda, Begam and Elamvazuthi, 2021).

2.3 Feature Classification

Within various conditions, a classification model is being used to determine the right voice speaking style. The strong pattern classification scheme is being educated through appropriately labelled illustrations in speech recognition.

The Hidden Markov Model (HMM) (Yoon, 2009; Cuiling, 2016; Xue 2018) is a mathematical method that might be used to explain how measurable phenomena evolve over time. Particular characteristics, which are not really easily detectable, play a role in this. The observable element influencing the occurrence is referred to as a 'state,' whereas the observable phenomenon is referred to as a 'symbol'. The unidentifiable procedure of unidentified conditions and the transparent methodology of measurable signs are the two stochastic systems that make up an HMM. That invisible conditions construct a Markov chain, and perhaps the detected sign's probability distribution will be determined by the corresponding system's probability distribution. Mostly as result, a doubly-embedded random variable is another name about an HMM. (Aymen, Abdelaziz, Halim and Maaref, 2011; Gales, 2009; Abushariah, Gunawan, Khalifa and Abushariah, 2010).

It is extremely sufficient to define findings within those 2 phases, one transparent and the other hidden. Although several real-world problems include categorising unstructured data into a set of classification or membership functions. That matters to them as well. Remember the issue of voice recognition, where this HMMs had already long been shown. Forecasting the spoken phrase from such a registered voice signal will be the aim of speech recognition. According to interpretations, the voice recognition system attempts to locate the series of consonant conditions that resulted in the real spoken voice. Although real transcription can vary greatly, the basic phonetic symbols cannot be detected explicitly and must be expected (Yoon, 2009; Cuiling, 2016; Xue, 2018).

Simulating biochemical components including such proteins and Genetic material may also prove to be valuable. The biochemical series is usually composed of small structural elements with specific properties and specific structural areas also have various measurement characteristics. As example, proteins are quite well for having several substances. Predicting the representing influences and specific positions throughout the amino acid composition for a specific protein will be important. It would always want to figure out what other protein community this specific protein series corresponds within. HMMs were shown to be highly successful at describing biochemical structures. This is used to template signal data with effectiveness. Mostly as consequence, HMMs have grown in popularity in theoretical cell genetics, with several cutting-edge sequence alignment methods rely on them (Yoon, 2009; Cuiling, 2016; Xue, 2018).

2.4 N - Gram

The N-gram is a texting-gram structure in which the "N" objects from a provided series or series are continuously arranged. Text mining, communication theory, text probability, and data compression are only a few of the areas where it is used. When assigning with varying probabilities, the N-gram is useful. That is because it assists in deciding which N-grams have the greatest chance of chunking together to create a single entity (Gadag and Sagar, 2016; Takahashi and Morimoto, 2012).

The N-gram analysis shows the appearance of an interpretive structural on the appearance of N-1 preceding terms. Unigram (N), bigram (N=2), trigram (N=3), and so on are all examples of N-grams. Bigram model N=2 predicts a term occurring based on the previous single word (N-1) and bigram model N=3 forecasts a term phenomenon based on the previous two terms (N-2) (N-2) (Ito and Kohda, 1996; Hatami, Akbari and Nasersharif, 2013).

3.0 METHODOLOGY

3.1 Speech Recognition Process

This overall system process is separated into 2 stage including as adapting stage and decoding stage. For adapting stage, 50 individual phrases of utterances by five separate speakers may also being used to adjust the Malaysian English language acoustic model utilising two adaptation strategies, MLLR and MAP. At first, all the speech sample will be collected and convert them into Mel Frequency Cepstral Coefficients (MFCC) format by undergoes the feature extraction. This feature extraction process will extract the main speech information and critical characteristic that is required for the system. So, all the MFCC files with extracted feature are produced. These MFCC files, list of transcripts of the adaption speech samples, list of speech sample filenames, and acoustic model were used in the adaptation.

Maximum Likelihood Linear Regression (MLLR) (Lestari and Irfani, 2015; Oh, Yoon and Kim, 2007) would be the first adaptation algorithm inspired. Through analysing that acoustic model's mean and variance, MLLR can predict and determine that optimum probability distribution and characteristics. Maximum A-Posteriori (MAP) has been the second adaptation approach applied. MAP performs nearly the similar purpose as MLLR, with the exception that it considers the prior throughout the prediction. The mixture weight and the transition matrices are also observed by MAP in addition to the acoustic model's variance and means. MAP updates the characteristics in the acoustic model, contrasting MLLR, which just generates a matrix that could be passed to the system upon decoding. Furthermore, while MAP appears to become a preferable adaptation approach, that alone necessitated a large amount of data for adaptation in attaining the desired prediction performance. Although MLLR proved possible to provide a noticeable enhancement in recognition rate with small dataset, two adaption methods were used in this study, one simultaneously and one individually, to examine respective impact on speech recognition application efficiency.

Prior beginning the decoding stage, those speech samples utilized to analyse the results were first feature extracted by MFCC. This speech recognition system then uses the created MFCC files, including comprise all extracted feature, customised acoustic model, MLLR matrices, language model, and dictionary model, to conduct speech recognition. After the decoding stage, all the result will be analysed by Sphinxtrain modules with Perl to measure the Word Error Rate (WER), Word Recognition Rate (WRR) and Sentence Error Rate (SER). Regarding comparison purposes, the system's functionality is evaluated under various conditions, such as without adaptation, with MLLR adaptation only, with MAP adaptation solely, and with combined MAP and MLLR adaptation.

3.2 Model Adaptation

Adaptation was employed throughout this research to increase the program's speech recognition performance. 5 separate people's voice samples and one internet-based conversation containing 50 different sentences. For adaption, many of these voice samples were obtained from typical conversations with five different people, as well as a presentation for one online speech. That work was completed using Sphinxtrain and Sphinxbase. Maximum Likelihood Linear Regression (MLLR) and Maximum A-Posteriori (MAP) were really the two adaption strategies used.

Typically implemented to the means through one or perhaps more Gaussian Mixture Models, this MLLR method determines a linear transformation. Pertaining to such models, this also maximises the probability of a sample of information. On the other hand, MAP is a sort of enhancement in which the functional form represents the likelihood of an outcome based (or symbol, or sequence) on prior information. That would be the likelihood with that occurrence, consistent with past prediction with that event's possibility (prior probability

distribution) and one or perhaps more occurrences. Furthermore, MLLR adaptation is convenient and ideal for limited sample adaption, but MAP adaptation needs additional sample to achieve the desired precision.

These MLLR matrix and customised acoustic models are again incorporated and modified correspondingly only with initial acoustic model. These procedures necessary to finish the adaption are as follows. Furthermore, the customization was carried out using command prompt.

1. To prepare the list of speech sample, these lists of speech sample is saved into the text file with Unix (LF) format and 8-bit data (UTF-8). To fulfil these formats, the notepad ++ is used to setting the list of speech sample. After that, the text file is converted to the .fields file format. Example of the list of the speech sample is showed at below (example only showed a part of this file):

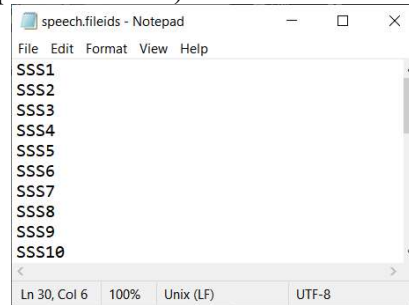


Figure 2. Sample of the list of the speech sample

2. To prepare the transcript of the speech sample, these transcripts of speech sample is saved into the text file with Unix (LF) format and 8-bit data (UTF-8). To fulfil these formats, the notepad ++ is used to setting the transcript of speech sample. The symbol "<s>" must added in front of each sentence and symbol "</s> (filename)" must added end of each sentence. Moreover, the word in transcription should be lower case and avoid use any symbol. After that, the text file is converted to the .transcription file format. Example of the list of the speech sample is showed at below (example only showed a part of this file):

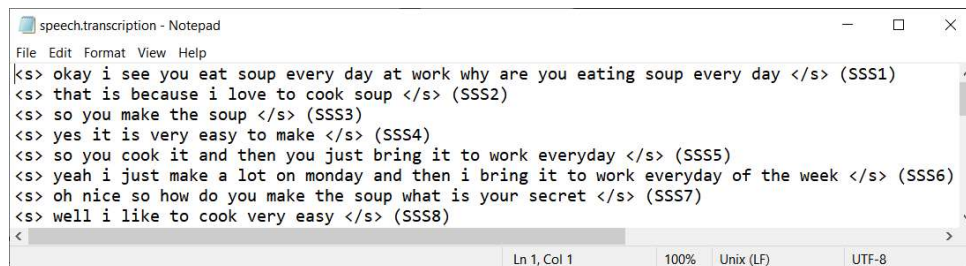
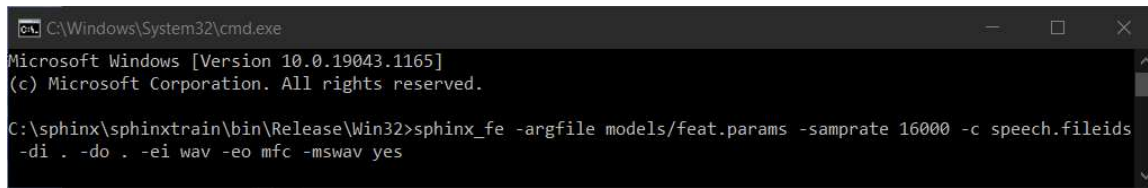


Figure 3. Sample of the transcript of the speech sample

3. After prepared the field and transcript file, all the fields file, transcription file, speech samples, original acoustic model, language model and dictionary model are copied into the working directory folder. The bw.exe, map_adapt.exe and mllr_solve.exe are required for the adaptation process.
4. Open the command prompt at the directory folder, then run the feature extraction tool which is sphinx_fe.exe in Sphinxbase. This tool was converting all the speech sample audio file from WAV file to MFC file, so the MFC files are produced which contain the essential information of speech samples. Moreover, it is really critical to check

that the parameters in the feat file match the default parameters. Because the tool was required the feat to operated. The code which is used to run feature extraction tool is showed at below:



```
C:\Windows\System32\cmd.exe
Microsoft Windows [Version 10.0.19043.1165]
(c) Microsoft Corporation. All rights reserved.

C:\sphinx\sphinxtrain\bin\Release\Win32>sphinx_fe -argfile models/feat.params -samprate 16000 -c speech.fileids
-di . -do . -ei wav -eo mfc -mswav yes
```

Figure 4. Code used to convert WAV audio files to MFC files format

5. To convert the mdef file into text file for the later collect observation count, the Pocketsphinx will used to do this process. This text file is important for next step. The code for conversion will show at below:

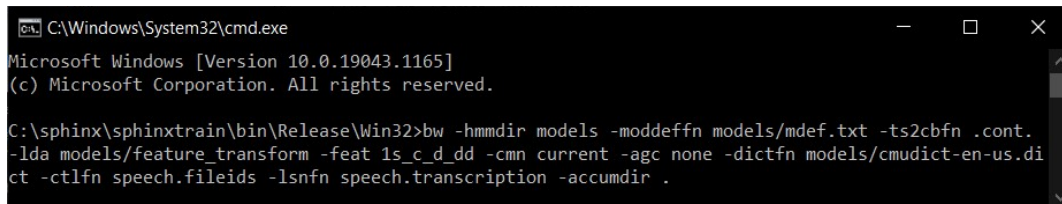


```
C:\Windows\System32\cmd.exe
Microsoft Windows [Version 10.0.19043.1165]
(c) Microsoft Corporation. All rights reserved.

C:\sphinx\sphinxtrain\bin\Release\Win32>pocketsphinx_mdef_convert -text models/mdef models/mdef.txt
```

Figure 5. Conversion of the mdef file to text file

6. For later adaptation, the observation count for the adaptation data was collected. The bw.exe program will collect accumulative observation count of the adaptation data. After the bw.exe program operated, the dictionary must be updated to include the word prognostication. The code for collect accumulative observation count of the adaptation data is showed at below:

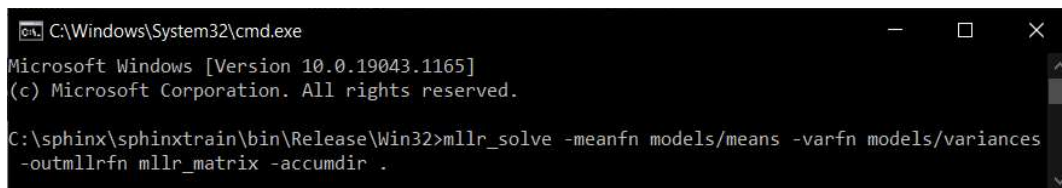


```
C:\Windows\System32\cmd.exe
Microsoft Windows [Version 10.0.19043.1165]
(c) Microsoft Corporation. All rights reserved.

C:\sphinx\sphinxtrain\bin\Release\Win32>bw -hmmdir models -moddeffn models/mdef.txt -ts2cbfn .cont.
-lda models/feature_transform -feat ls_c_d_dd -cmn current -agc none -dictfn models/cmudict-en-us.di
ct -ctlfn speech.fileids -lsnfn speech.transcription -accumdir .
```

Figure 6. Code used to collect the statistics data from the adaptation data

7. Code was used to apply MLLR adaptation to the acoustic model which is showed at below. The decoder will receive an MLLR transformation matrix, which should be handed to it during the decoding process.



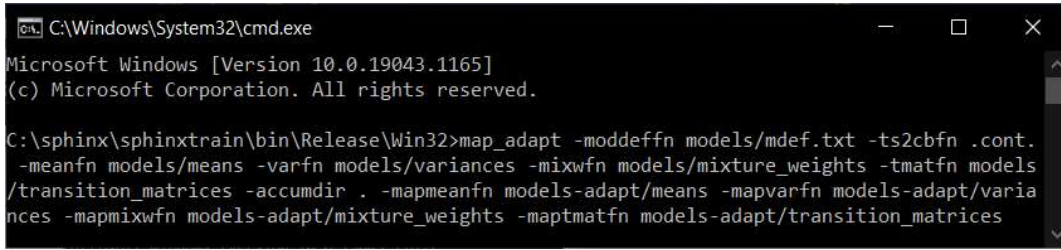
```
C:\Windows\System32\cmd.exe
Microsoft Windows [Version 10.0.19043.1165]
(c) Microsoft Corporation. All rights reserved.

C:\sphinx\sphinxtrain\bin\Release\Win32>mllr_solve -meanfn models/means -varfn models/variances
-outmllrfn mllr_matrix -accumdir .
```

Figure 7. Code used for MLLR adaptation

8. Code was used to apply MAP adaptation to the acoustic model. The parameters including means, variance, mixture weight, and transition matrices from the original

acoustic model were used to create an adapted acoustic model. Following adaptation, this will be replaced with the latest parameters. The code used to operate the MAP adaptation which is showed at below:

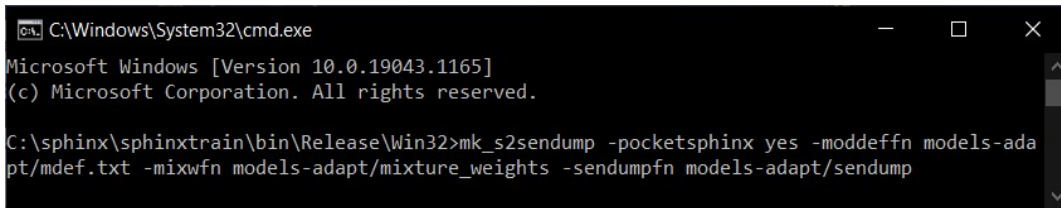


```
C:\Windows\System32\cmd.exe
Microsoft Windows [Version 10.0.19043.1165]
(c) Microsoft Corporation. All rights reserved.

C:\sphinx\sphinxtrain\bin\Release\Win32>map_adapt -moddefn models/mdef.txt -ts2cbfn .cont.
-mapfn models/means -varfn models/variances -mixwfn models/mixture_weights -tmatfn models
/transition_matrices -accumdir . -mapmeanfn models-adapt/means -mapvarfn models-adapt/varia
nces -mapmixwfn models-adapt/mixture_weights -mapmatfn models-adapt/transition_matrices
```

Figure 8. Code used for MAP adaptation

9. The measured and modified mixture_weights are saved in a sendump file, which is compatible by Pocketsphinx. When starting the script with the adapted mixture_weights, this could be replicated. To reduce the storage used by the adapted acoustic model, applied the mk_s2sendump. This process will replace the sendump file with improve the mixture_weights. The code for this process is showed at below:



```
C:\Windows\System32\cmd.exe
Microsoft Windows [Version 10.0.19043.1165]
(c) Microsoft Corporation. All rights reserved.

C:\sphinx\sphinxtrain\bin\Release\Win32>mk_s2sendump -pocketsphinx yes -moddefn models-ada
pt/mdef.txt -mixwfn models-adapt/mixture_weights -sendumpfn models-adapt/sendump
```

Figure 9. Code used to rebuild the adapted sendump file

This initial acoustic framework was updated with the adapted acoustic model when all of the stages were finished. Furthermore, most of the code that has been utilised was put into a batch file for convenient processing.

4.0 RESULT AND DISCUSSION

Overall effectiveness of speech recognition is compared with a popular measurement defined as Word Error Rate (WER) to determine the functionality including its produced speech recognition system. WER is calculated through using words of speech, as stated with in equation following.

$$\text{Word Error Rate (WER)} = \frac{\text{Substitutions (S)} + \text{Insertions (I)} + \text{Deletions (D)}}{\text{Number of Word in the reference (N)}}$$

This would calculate the amount of words which are substituted, deleted from its transcription, and unsaid words which are already inserted to evaluate the effectiveness about an automatic speech recognition system. Word Recognition Rate (WRR) and Sentences Error Rate (SER) are two metrics that can be used to evaluate the effectiveness about an ASR system. Several metrics should be applied to evaluate how many words inside the comparison translation fit and how many phrases are erroneous.

The model adaptation will be trained and tested by 1 online presenter and 5 speakers. These speakers will help to adapt the acoustics models and testing the adapted models. For all

adapted transcription will used 50 sentences to adapt acoustics model and 30 sentences to test the adapted model.

4.1 Speech Recognition System performance test by using adaptation transcription

For the MAP average value, the Word Error Rate (WER) is 15.57%, the Word Recognition Rate (WRR) is 86.41% and the Sentence Error Rate (SER) is 64.97%. By comparison between the MAP and MLLR, the Word Error Rate (WER) of MAP is lesser than the MLLR with 31.39%, the Word Recognition Rate (WRR) of MAP is higher than MLLR with 22.29% and the Sentence Error Rate (SER) of MAP is lower than MLLR with 32.47%. This comparison showed that Word Error Rate (WER) and Sentence Error Rate (SER) of MAP have much smaller compare with MLLR and the Word Recognition Rate (WRR) have very large improvement compare with MLLR. The MAP is better than MLLR in improve accuracy around 20% and reduce mistake for the speech recognition system around 30%.

For both adaptation with MAP and MLLR average value, the Word Error Rate (WER) is 17.94%, the Word Recognition Rate (WRR) is 88.84% and the Sentence Error Rate (SER) is 70.83%. By comparison between both adaptation and MAP, the Word Error Rate (WER) of both adaptation is more than the MAP with 2.37%, the Word Recognition Rate (WRR) of both adaptation is higher than MAP with 2.44% and the Sentence Error Rate (SER) of both adaptation is higher than MAP with 5.86%. This comparison showed that both adaptations have improved the accuracy of the speech recognition system, but it also increases the error rate of the speech recognition system by comparing with MAP. The increase of Sentence Error Rate (SER) is much higher compare Word Recognition Rate (WRR) by comparing both adaptation and MAP.

In conclusion, the MAP adaptation method is best choice for the speech recognition system, and it is highest improvement in accuracy with lowest error rate for the speech recognition system. Even through, both adaptations method has the highest Word Recognition Rate (WRR) but the Word Error Rate (WER) and Sentence Error Rate (SER) also increased. The increase of the error rate is much higher compare with recognition rate for both adaptation method.

Table 1. Output result for average with adaptation transcription

	Word Error Rate (WER)	Word Recognition Rate (WRR)	Sentence Error Rate (SER)
Original	55.10%	58.25%	97.44%
MLLR	46.96%	64.12%	97.44%
MAP	15.57%	86.41%	64.97%
MLLR and MAP	17.94%	88.84%	70.83%

4.2 Speech Recognition System performance test by using test transcription

For the MAP average value, the Word Error Rate (WER) is 32.84%, the Word Recognition Rate (WRR) is 72.52% and the Sentence Error Rate (SER) is 78.89%. By comparison between the MAP and MLLR, the Word Error Rate (WER) of MAP is lesser than the MLLR with 18.55%, the Word Recognition Rate (WRR) of MAP is higher than MLLR with 12.79% and the Sentence Error Rate (SER) of MAP is lower than MLLR with 18.33%. This comparison showed that Word Error Rate (WER) and Sentence Error Rate (SER) of MAP have much smaller compare with MLLR and the Word Recognition Rate (WRR) have very large improvement compare with MLLR. The MAP is better than MLLR in improve accuracy around 12% and reduce mistake for the speech recognition system around 18%.

For both adaptation with MAP and MLLR average value, the Word Error Rate (WER) is 48.01%, the Word Recognition Rate (WRR) is 61.97% and the Sentence Error Rate (SER) is 78.89%.

is 81.67%. By comparison between both adaptation and MAP, the Word Error Rate (WER) of both adaptation is more than the MAP with 15.17%, the Word Recognition Rate (WRR) of both adaptation is lower than MAP with 10.55% and the Sentence Error Rate (SER) of both adaptation is higher than MAP with 2.78%. This comparison showed that both adaptations have reduced the accuracy of the speech recognition system and it also further increases the error rate of the speech recognition system by comparing with MAP.

In conclusion, the MAP adaptation method is also best choice for the speech recognition system with test transcription, and it have highest improvement in accuracy with lowest error rate for the speech recognition system. The accuracy of both adaptation method is decreased compare with MAP by using test transcription and this case is not similar compare with adaptation transcription. By using adaptation transcription, both adaptation method is showed the improvement of the accuracy, but it also increases the error rate. That adaptation method showed the accuracy decrease and further improve the Word Error Rate (WER) by using test transcription.

Table 2. Output result for average with test transcription

	Word Error Rate (WER)	Word Recognition Rate (WRR)	Sentence Error Rate (SER)
Original	58.55%	54.36%	97.22%
MLLR	51.39%	59.73%	97.22%
MAP	32.84%	72.52%	78.89%
MLLR and MAP	48.01%	61.97%	81.67%

5.0 CONCLUSION

In conclusion, adaptation and test scripts were used to evaluate the effectiveness of the constructed speech recognition system. For testing this system by using adaptation transcription, the MAP adaptation method has showed the high accuracy with lowest error rate. The MAP has the lowest Word Error Rate (WER) and lowest Sentence Error Rate (SER) with 15.57% and 64.97%. The MAP also has high Word Recognition Rate (WRR) with 86.41%. But the Word Recognition Rate (WRR) of MAP adaptation method is lower than both adaptation method and the different of them is 2.44%. Both adaptation method also will increase the Word Error Rate (WER) and Sentence Error Rate (SER) compare with MAP adaptation method. The improvement accuracy of both adaptation method is lower compare with increment of error rate. The MLLR adaptation method is showed the worst improvement in accuracy and error rate compare with MAP and both adaptation method. So, the MAP is best choice for adaptation transcription.

For testing transcription, the MAP adaptation method is showed the highest accuracy and lowest error rate for speech recognition system. The Word Error Rate (WER) of MAP adaptation method is 32.84%, the Word Recognition Rate (WRR) is 72.52% and the Sentence Error Rate (SER) is 78.89%. Moreover, both adaptation method has second higher accuracy and second lower error rate. Both adaptation with test transcription have showed the decrease accuracy and increase error rate compare with adaptation transcription. The MLLR adaptation method is showed the worst improvement in accuracy and error rate compare with MAP and both adaptation method.

Finally, the MAP adaptation method is suitable for adaptation and test transcription. The MAP adaptation method is best adaptation method, and it will be implemented into speech recognition system. This Malaysian English speech recognition system's weakness is that it may function poorly if somehow the voice stream includes a lot of distortion and noise. Whereas if surroundings are noisy, this system may not achieve sufficient performance.

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